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Comparing the effects of climate and land use on surface water quality using future watershed scenarios

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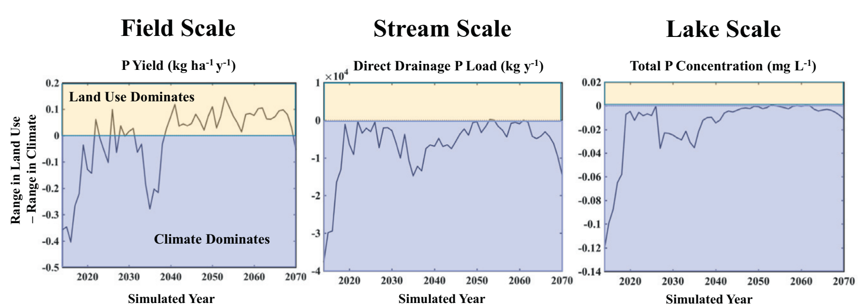
HIGHLIGHTS

- Climate had a stronger influence than land use on three water quality indicators.
- Land use effects were still significant across multiple decades and robust to climate.
- The effects of land use attenuated when moving from field to stream to lake.
- Reducing over-application of P was an effective management strategy.

GRAPHICAL ABSTRACT



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ABSTRACT

Eutrophication of freshwaters occurs in watersheds with excessive pollution of phosphorus (P). Factors that affect P cycling and transport, including climate and land use, are changing rapidly and can have legacy effects, making future freshwater quality uncertain. Focusing on the Yahara Watershed (YW) of southern Wisconsin, USA, an intensive agricultural landscape, we explored the relative influence of land use and climate on three indicators of water quality over a span of 57 years (2014–2070). The indicators included watershed-averaged P yield from the land surface, direct drainage P loads to a lake, and average summertime lake P concentration. Using biophysical model simulations of future watershed scenarios, we found that climate exerted a stronger influence than land use on all three indicators, yet land use had an important role in influencing long term outcomes for each. Variations in P yield due to land use exceeded those due to climate in 36 of 57 years, whereas variations in load and lake total P concentration due to climate exceeded those due to land use in 54 of 57 years, and 52 of 57 years, respectively. The effect of land use was thus strongest for P yield off the landscape and attenuated in the stream and lake aquatic systems where the influence of weather variability was greater. Overall these findings underscore the dominant role of climate in driving inter-annual nutrient fluxes within

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the hydrologic network and suggest a challenge for land use to influence water quality within streams and lakes over timescales less than a decade. Over longer timescales, reducing applications of P throughout the watershed was an effective management strategy under all four climates investigated, even during decades with wetter conditions and more frequent extreme precipitation events.

1. Introduction

Eutrophication of surface waters due to phosphorus (P) enrichment is a worldwide concern driven by multiple interacting factors. Some factors affecting water quality are stable over decades and centuries, such as geology, soil texture, and topography (Kyllmar et al., 2006), but other factors can change quickly in response to human activities (Vanni et al., 2001). These more immediate factors include land use type and intensity (Puckett, 1995; Gergel et al., 2002; Johnson et al., 1997; Tong and Chen, 2002; Smith et al., 2013), composition and configuration of land cover (O'Neill et al., 1997; Clément et al., 2017), management practices (Sharpley et al., 1994; Crossman et al., 2016), engineering structures that alter nutrient flows (Jarvie et al., 2006; Gentry et al., 2007; Arnscheidt et al., 2007), and changes in climate and hydrology (Michalak, 2016). Many or all of these factors may be shifting simultaneously over a given period, making it difficult to attribute changes in water quality to any one factor (Gillon et al., 2016). Continued change in these factors challenges our ability to manage landscapes in ways that promote clean water.

Nonpoint source pollution from agriculture is a primary factor contributing to the impairment of freshwater ecosystems (Carpenter et al., 1998). As such, water quality remediation efforts in many agricultural watersheds have focused on best management practices (BMPs) that decrease nutrient runoff from agricultural lands (Sharpley, 2016). However, the effectiveness of BMPs has varied widely within and among watersheds (Baker and Richards, 2002; Jordan et al., 2005, 2007; Fiener and Auerswald, 2009; Carvin et al., 2018; Renwick et al., 2018). At the field scale, agricultural and nutrient management programs have reduced P losses, but there has been less reported success at stream and watershed scales (Meals et al., 2010; Jarvie et al., 2013a, 2013b), and limited evaluation of land use practices at the watershed scale (Sharpley et al., 2009). Thus, there exists a research gap in understanding changes in water quality due to land use and land management across spatial scales, including questions related to the magnitude and timing of responses to changes in management practices (Sharpley et al., 2009; Wood et al., 2005). Even though there are different dimensions of land use and cover (e.g. composition and spatial configuration of land cover, land use type, and land use intensity), here we broadly define land use as an aggregate term that encompasses all aspects of land use, cover, and management.

In addition to the effects of land use, climate change may also substantially alter freshwater quality by changing fluxes of water and P as well as bringing warmer temperatures that favor the growth of harmful algal blooms (Gkelis et al., 2014; Michalak, 2016). Nutrient transport can be altered as the timing and magnitude of runoff and soil moisture, lake levels, groundwater availability, and river discharge regimes change (Bates et al., 2008; Crossman et al., 2016). Increases in rainfall intensity can increase loading of sediment and P to surface waters (Haygarth and Jarvis, 1997; Royer et al., 2006; Carpenter et al., 2014; Gonzalez-Hidalgo et al., 2013; Motew et al., 2018).

While future projections of climate and land use are fraught with uncertainty (Carpenter et al., 2006), changes in both drivers are likely to affect water quality outcomes across spatial and temporal scales in the future. Already there is evidence of this, for example in the Lake Erie Basin, where a concerted effort to implement BMPs over the past two decades has been counteracted by changes in both agricultural practices and climate (Michalak et al., 2013). These included an increased use of tile drainage, an efficient subsurface transport mechanism of dissolved P to surface water bodies; increased surface losses of dissolved P stemming from conservation tillage; and greater frequency of extreme rain events (Michalak et al., 2013). Lake Erie's water quality has remained poor, resulting in several years in the 2010s having massive, harmful cyanobacteria blooms (Michalak et al., 2013). Another watershed exhibiting a diversity of effects from both land use and climate is the Yahara Watershed (YW) of southern Wisconsin, where BMPs have been implemented with little impact on water quality (Lathrop, 2007). Several counteracting factors have been blamed, including the intensification of dairy agriculture (Gillon et al., 2016), increased frequency of heavy rain events (Kucharik et al., 2010), as well as the gradual release of legacy P from soils and sediments (Motew et al., 2017).

In this study we aim to understand the challenges and opportunities occurring at a local level to improve water quality in the face of future uncertainty. Because climate change is driven by human activities occurring at a global scale, land use represents an important avenue by which managers and decision makers at a local scale can affect outcomes of water quality. Here we used biophysical models to study climate and land use effects on three watershed indicators of water quality, bypassing the limitations of physical experimentation and observation at the watershed scale. We simulated long-term (57 year) future scenarios of climate and land-use change for the Lake Mendota watershed, an exemplar of urbanizing agricultural watersheds. We asked: (1) What is the relative importance of variable climate and land use on three distinct water quality indicators, including average P yield from the watershed land surface, direct drainage stream P loads to a lake, and average total P concentration in the lake? And (2) Are there land use strategies that are effective under various future climates? Answers to these questions were intended to provide perspective on the potential for local action to affect surface water quality and thus inform watershed management and goal-setting in the face of climate change.

2. Methods

2.1. Study area

The 1345 km^2 Yahara Watershed of southern Wisconsin encompasses a chain of eutrophic lakes: Mendota, Monona, Waubesa, and Kegonsa, connected by the Yahara River. The 686 km^2 subwatershed of Lake Mendota, the largest and furthest upstream lake of the chain, is our study region. Roughly 63% of the Lake Mendota Watershed is devoted to agriculture, with corn, soy, and dairy being the principal products. The Wisconsin state capital city of Madison (43°6′N, 89° 24′W) and surrounding urban area comprises roughly one quarter of the watershed and is centered on an isthmus between Lakes Mendota and Monona. The remaining portions of the watershed are covered in natural vegetation, including forest, wetland, and prairie. The Lake Mendota Watershed is characterized by relatively flat slopes (~4%) and silt loam soils. Nonpoint pollution reduction programs, including the use of best management practices, have been ongoing for several decades, however lake water quality has not improved (Lathrop and Carpenter, 2013). Lack of improvement has been attributed to the intensification of dairy production, an increase in precipitation and frequency of extreme rain events, as well as the slow release of legacy P from soils and sediments (Gillon et al., 2016; Motew et al., 2017).

2.2. Description of models

The biophysical modeling framework included Agro-IBIS (Integrated Biosphere Simulator), a terrestrial ecosystem model; THMB (Terrestrial Hydrology Model with Biogeochemistry), a hydrologic and nutrient routing model; and the Yahara Water Quality (WQ) Model, which estimates water quality indicators in the four mainstem Yahara lakes. Agro-IBIS simulates the movement of water, energy, momentum, carbon, nitrogen, and phosphorus in both natural and managed ecosystems. The structure of Agro-IBIS has been described in detail (Foley et al., 1996; Kucharik et al., 2000; Kucharik, 2003), and many components of the model have been validated across a range of ecosystems at various spatial and temporal scales (El Maayar et al., 2001; Kucharik and Brye, 2003; Kucharik et al., 2006; Kucharik and Twine, 2007; Soylu et al., 2014; Zipper et al., 2015). Recently, biogeochemical cycling of P was added to Agro-IBIS to enable field scale simulation of P loss to runoff, i.e. P yield, an indicator of surface water quality. The terrestrial P module in Agro-IBIS includes P application, transformation, and loss of dissolved P to runoff; in-soil cycling of organic and inorganic forms of P; and loss of particulate-bound P with erosion.

Agro-IBIS is coupled to THMB, a physically-based hydrologic routing model that simulates transport of water, sediment, and P at the watershed scale, including in-channel sediment P erosion and deposition and delivery of P loads to the YW lakes. THMB links topographic data and river morphological characteristics within the stream network to a set of linear reservoir functions, thereby simulating temporal variability of water flow and storage in the hydrologic system (Coe, 1998, 2000; Coe et al., 2008). Phosphorus transport is simulated by THMB, including both sediment and dissolved forms (Donner et al., 2002; Motew et al., 2017). The sediment transport functions in THMB are based on a fine sediment transport model (Patil et al., 2012), appropriate for the silt loam soils that dominate the watershed. Dissolved P is treated as a conservative solute. Both forms of P are governed by mass balance.

Direct drainage loads of P from THMB are passed to the Yahara WQ Model which predicts summer water quality variables in the four mainstem Yahara lakes. The water quality variables represent averages over the months of July and August, when water quality is especially vulnerable to eutrophication but important to lake users. The model computes a mass balance for each lake using empirical relationships (Carpenter and Lathrop, 2014). Total annual loads to Lake Mendota are calculated based on direct drainage loads. Summer (July–August) water quality is computed using empirical regressions based on terms of the P mass balance (Lathrop and Carpenter, 2013; Carpenter and Lathrop, 2014). All annual quantities are computed for the November 1st–October 31st time period, corresponding to late fall when the lake is well-mixed. Development and validation of the entire model framework including Agro-IBIS, THMB, and the Yahara WQ Model, can be found in Motew et al. (2017).

2.3. Scenarios

Because of the long residence time and slow movement of P through watersheds (Hamilton, 2012; Sharpley et al., 2013), understanding changes in water quality requires a long-term perspective. To conduct this research, we used 57-year future watershed scenarios as inputs to biophysical models. The Yahara 2070 scenarios were designed to explore possible trajectories from 2014 to the year 2070 in the Yahara Watershed (hence 57 years) under different regimes: no action on environmental trends that results in a disaster and regeneration of natural ecosystems ("Abandonment and Renewal"); accelerated technological development that is accompanied by urban growth ("Accelerated Innovation"); strong intervention by government that prioritizes water quality and perennial land cover types ("Nested Watersheds"); and shifting values toward sustainability that include grazing livestock ("Connected Communities") (Carpenter et al., 2015). The scenarios were developed through an iterative process of adapting archetypal drivers of global change to the perspectives, social processes, and environmental conditions of the Yahara watershed, within the constraints created by coupling the storylines with biophysical models (Carpenter et al., 2015; Booth et al., 2016). The scenarios were designed to be highly contrasting yet plausible, thereby covering a wide range in climate and land use outcomes. This made them suitable for examining the effects of land use and climate on water quality, and only required a limited number of simulations (16, see Section 2.4).

The four core scenarios were each comprised of a set of independent climate- and land-use-related driver datasets (Booth et al., 2016). We combined each land use and climate driver dataset in factorial fashion (i.e., 4 climate trajectories × 4 land use trajectories) to investigate a wide range of combinations. A detailed description of the scenario development process and the full scenarios themselves are given by Carpenter et al. (2015) and Booth et al. (2016). Consistent with the major themes of each core scenario, we refer to the individual land use trajectories (herein referred to as the land use scenarios) as *Nature*, *Urban*, *Grazing*, and *Biofuel*, which correspond to the original integrative

Table 1
Climate characteristics of the four climate scenarios (*C1–4*). The years 2014–2020 are used as decade 1 for ease of analysis.

	Climate scenario	Decade 1	Decade 2	Decade 3	Decade 4	Decade 5	Decade 6
		2014–2020	2021–2030	2031–2040	2041–2050	2051–2060	2061–2070
Mean Annual Prec (mm)	*C1*	1104	1002	961	922	1008	993
	C2	945	1068	1229	1156	877	891
	C3	900	1075	985	933	1089	963
	C4	1030	1056	1005	1012	795	846
Mean Annual Tmax (°C)	*C1*	15	16	16	16	16	16
	C2	16	17	18	17	20	20
	C3	16	16	17	17	17	18
	C4	16	17	17	18	18	18
Mean Annual Tmin (°C)	*C1*	3	4	4	4	5	5
	C2	5	6	7	7	9	8
	C3	5	5	6	6	7	7
	C4	5	6	6	7	7	7
# Weeks with 5″ or more total precip per decade	*C1*	4	8	13	10	3	1
	C2	3	7	6	5	5	11
	C3	5	7	5	7	7	6
	C4	10	5	6	7	7	3
Atmospheric CO_2 (ppm)	*C1*	407	431	461	494	524	547
	C2	419	456	506	561	621	683
	C3	412	439	477	517	562	605
	C4	414	443	484	528	577	625

scenarios termed Abandonment and Renewal, Accelerated Innovation, Connected Communities, and Nested Watersheds, respectively. The climate scenarios are likewise referred to as *C1*, *C2*, *C3*, and *C4*, respectively. While each climate scenario was unique and varied, covering a wide range of conditions, some distinguishing traits were present in each. For example *C1* included dramatic flooding in the 1930s and relatively stable temperatures throughout. *C2* featured wetter and progressively warmer conditions over the six decades. *C3* changed the least from present climate, and *C4* featured gradual warming and progressively drier conditions over the simulation period. Tables 1 and 2 provide key climatic and land use characteristics for each of the climate and land use scenarios.

2.4. Model simulations

We simulated all combinations of land-use and climate scenarios, for a total of $4 \times 4 = 16$ simulations. Because all varying model inputs were related to either climate or land use, there were no other potential causes of variation in model outputs. Translating the four core scenarios into climate and land use driver data consisted of (1) deriving daily weather inputs by combining climate model projections and a stochastic weather generator; and (2) spatially distributing annual, narrative-based watershed-scale land use/land cover using transition rules and associated annual manure and fertilizer inputs modified from current farm and livestock data (Booth et al., 2016). Land use inputs assigned at each grid cell included the land cover category (corn, soy, wheat, hay, pasture, alfalfa, urban, wetland, forest, and grassland), the Modified Universal Soil Loss Equation's C factor ("CFAC") which represents the effect of land cover and management on erosion (Williams, 1975), and nutrient application details (mass and percent dry matter content of P in manure). Manure P applications were made three times a year (winter, spring, and fall), and fertilizer P applied once at planting. Climate inputs included daily temperature, precipitation, wind speed, solar radiation, and relative humidity, as well as annual atmospheric CO_2 concentrations (Supp. Materials). More details on climate, land use, and nutrient applications can be found in Booth et al. (2016) and Motew et al. (2017).

Each of the 16 factorial simulations was run over the 2014–2070 time period. Prior to each scenario simulation, a 200-year spin-up was conducted to bring carbon and nitrogen pools to equilibrium in soils and tree biomass. The last 25 years of the spin-up were used to bring soil P pools to approximate equilibrium. Motew et al. (2017) first used this modeling framework to investigate the influence of soil legacy P on lake water quality in the Yahara watershed over the recent historical period (1986–2013). The historical driver data (pre-2014) used in that study were used here to perform the spin-up. The derivation of the historical driver data as well as the full model calibration and validation procedure are described in detail in Motew et al. (2017).

2.5. Analysis

For each land use scenario, land cover was only altered at the beginning of each decade. Thus we focused most of the analysis on decadal averages of the three water quality indicators. These indicators, obtained as model outputs that span the field-to-lake transport pathway, included watershed-averaged annual total P yield from the landscape (P yield, kg ha^{-1} y^{-1}), annual direct drainage stream P load to Lake Mendota (DDL, kg y^{-1}), and mean summertime total P concentration in Lake Mendota (TP, mg L^{-1}). The years 2014–2020 represented the baseline period and were treated as decade one in analyses. We first examined each water quality indicator by grouping by either land use scenario or climate scenario ($n = 4$ for each) and computing a mean value per decade. This is shown by the following equation that calculates the mean indicator response for a given climate scenario *C* where $\bar{I}_{C,D}$ is the average of the water quality indicator *I*, *L* is the land use scenario, and *D* is the decade:

$$\bar{I}_{C,D} = \frac{1}{4}\sum_{L=1}^{4} I_{C,L,D} \tag{1}$$

And similarly, for the average decadal response for a land use scenario *L*:

$$\bar{I}_{L,D} = \frac{1}{4}\sum_{C=1}^{4} I_{C,L,D} \tag{2}$$

Each land use and climate scenario was standardized in terms of its percent deviation from the mean, using the following equation to calculate a percent deviation of a given climate scenario *C* from the average land use scenario response $\bar{I}_{L,D}$:

$$DEV_{C,D} = 100\left(\frac{I_{C,L,D} - \bar{I}_{L,D}}{\bar{I}_{L,D}}\right) \tag{3}$$

and similarly, the percent deviation of a given land use scenario *L* from

Table 2
Percent land use category for each land use scenario (*Urban*, *Nature*, *Grazing*, and *Biofuel*).

Land use scenario	Land use category	Decade 1	Decade 2	Decade 3	Decade 4	Decade 5	Decade 6
		2014–2020	2021–2030	2031–2040	2041–2050	2051–2060	2061–2070
Urban	Corn/Soy/Veg	49%	48%	44%	48%	50%	51%
	Alfalfa/Hay/Wheat	14%	14%	16%	10%	5%	3%
	Pasture	1%	1%	1%	0%	0%	0%
	Developed	23%	24%	25%	29%	32%	34%
	Forest/Grass/Wetland	14%	13%	14%	12%	12%	11%
Natural	Corn/Soy/Veg	49%	49%	36%	22%	14%	19%
	Alfalfa/Hay/Wheat	14%	13%	6%	3%	10%	13%
	Pasture	1%	1%	1%	2%	4%	5%
	Developed	23%	25%	23%	19%	7%	7%
	Forest/Grass/Wetland	13%	13%	33%	54%	64%	56%
Pasture	Corn/Soy/Veg	49%	47%	38%	29%	27%	28%
	Alfalfa/Hay/Wheat	14%	14%	15%	16%	18%	18%
	Pasture	1%	1%	6%	14%	15%	16%
	Developed	23%	23%	24%	22%	20%	17%
	Forest/Grass/Wetland	14%	15%	16%	19%	20%	20%
Biofuel	Corn/Soy/Veg	49%	48%	44%	38%	11%	9%
	Alfalfa/Hay/Wheat	14%	14%	16%	18%	33%	32%
	Pasture	1%	1%	1%	1%	4%	4%
	Developed	23%	23%	24%	25%	25%	25%
	Forest/Grass/Wetland	14%	14%	15%	17%	28%	30%

the average climate scenario response $\bar{I}_{C,D}$ was calculated with:

$$DEV_{L,D} = 100\left(\frac{I_{C,L,D} - \bar{I}_{C,D}}{\bar{I}_{C,D}}\right) \tag{4}$$

We compared the relative impacts of climate and land use using the range in each annual-scale indicator as observed across each scenario. The range due to climate across a given land use scenario L was calculated as:

$$R\_CLIM_{L,Y} = \ max(I_{L,1,Y}, I_{L,2,Y}, I_{L,3,Y}, I_{L,4,Y}) - \ min(I_{L,1,Y}, I_{L,2,Y}, I_{L,3,Y}, I_{L,4,Y}) \tag{5}$$

where I represents the water quality indicator for land use scenario L, climate scenario 1–4, and year Y. For the range due to land use across a given climate scenario, a similar equation was used:

$$R\_LU_{C,Y} = \ max(I_{C,1,Y}, I_{C,2,Y}, I_{C,3,Y}, I_{C,4,Y}) - \ min(I_{C,1,Y}, I_{C,2,Y}, I_{C,3,Y}, I_{C,4,Y}) \tag{6}$$

where I represents the water quality indicator for land use scenario 1–4, climate scenario C, and year Y. All analyses were conducted using MATLAB (The MathWorks, Inc., 2015).

3. Results

3.1. Outcomes of water quality indicators: decadal responses

Mean annual P yield, DDL, and TP followed similar trajectories when averaged over the six decades and grouped by land-use scenario

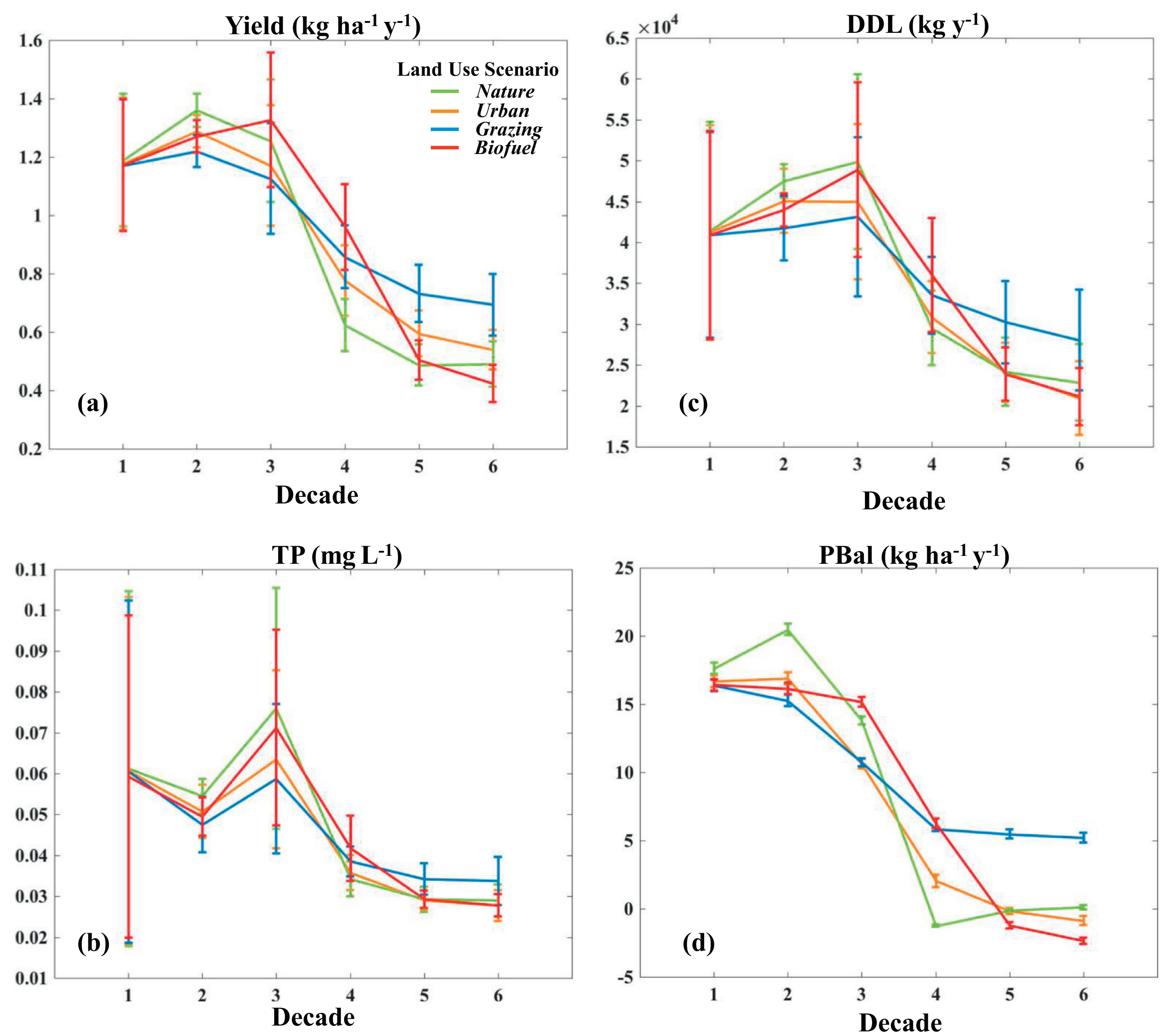

Fig. 1. Mean decadal trends in water quality variables under the four land use scenarios. (a)–(c) are water quality indicators (model outputs), including watershed-averaged total P yield (kg ha^{-1} y^{-1}), mean annual direct drainage load (DDL, kg y^{-1}), and mean summertime total P concentration in Lake Mendota (TP, mg L^{-1}), respectively. (d) shows the net balance of P inputs to the soil system, a combination of model inputs and simulated harvest rate: PBal = mean annual manure rate + fertilizer rate − harvest rate (kg ha^{-1} y^{-1}). Error bars represent one standard deviation in the range across the four climate scenarios, *C1–4*. The baseline period, 2014–2020, is shown as decade one.

(Fig. 1a–c). The general trajectory showed each P response variable peak in the third decade, and then decrease over the last four decades. The highest value of mean annual P yield occurred in decade two of the *Nature* scenario, whereas the lowest value of P yield occurred in the last decade in the *Biofuel* scenario. For DDL and TP, the highest values both occurred in decade three for the *Nature* scenario. The lowest values of DDL and TP both occurred in decade six for the *Biofuel* scenario, representing the best overall decade for stream and lake water quality.

The standard deviation in P yield, DDL, and TP, indicated by error bars in Fig. 1, reflected the range in response due to climate variation in each decade. For P yield, the least variation due to climate occurred in *Grazing* during decade two, and the most variation occurred in *Biofuel*

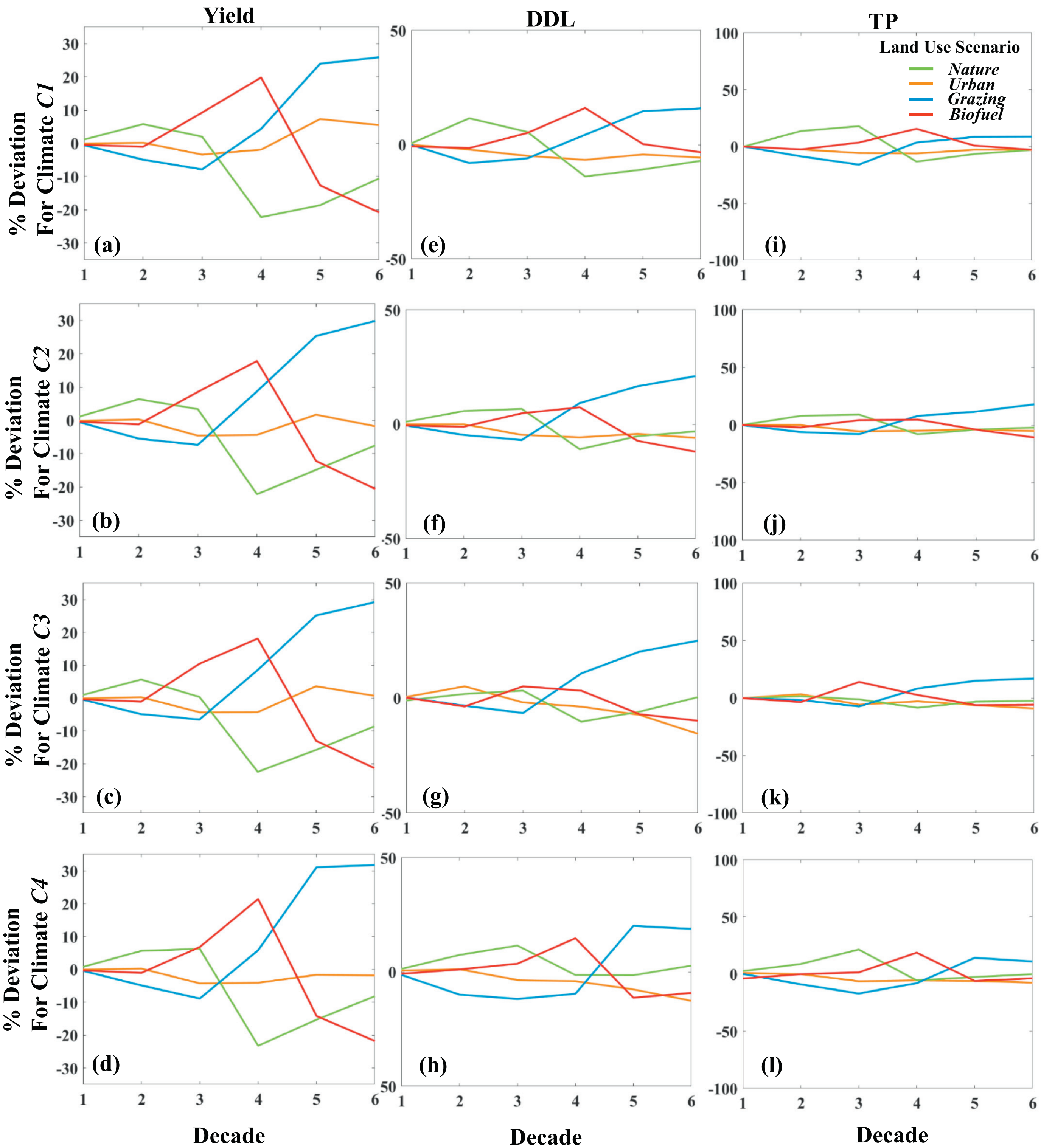

Fig. 2. Percent deviation from the climate-averaged mean for each land use scenario in decades 1–6. First column is watershed-averaged total P yield, second column is direct drainage load to Lake Mendota, and third column is summertime lake TP concentration in Lake Mendota. Rows correspond to the climate scenarios *C1*, *C2*, *C3*, and *C4*, in order of top to bottom, respectively.

during decade three. For DDL, the least variability due to climate occurred in *Biofuel* in the second decade, and the greatest variability during *Nature* in the first decade. For TP, decade five of *Biofuel* featured the least variability due to climate, while the first decade in *Nature* featured the greatest variability. A similar plot of decadal trends in water quality indicators, grouped by climate, is provided in Supp. Fig. 1.

3.2. Rankings of the four land use scenarios

Decadal trends in the four land use scenarios were assessed for P yield, DDL, and TP, in terms of percent annual deviation from the mean under a given climate (DEV_L in Eq. (4)) (Fig. 2). The deviations due to land use showed consistent trends across the climate scenarios

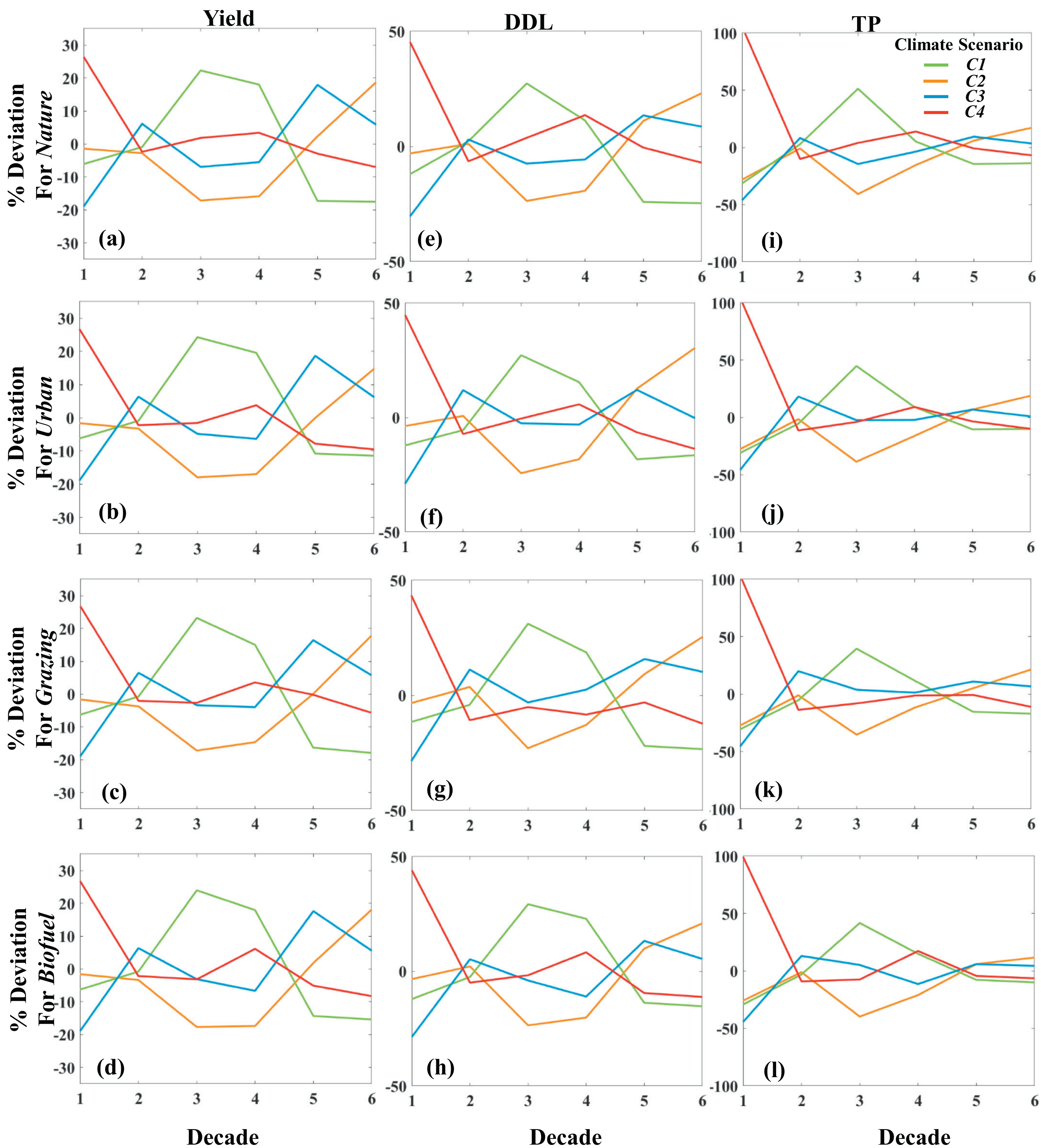

Fig. 3. Percent deviation from the land use-averaged mean for each climate scenario. First column is watershed-averaged total P yield, second column is direct drainage load to Lake Mendota, and third column is summertime lake TP concentration in Lake Mendota. Rows correspond to the land use scenarios *Nature*, *Urban*, *Grazing*, and *Biofuel*, in order of top to bottom, respectively. The baseline period, 2014–2020, is used as decade one.

(down each column) and across the three water quality indicators. The divergence in trends among land-use scenarios increased gradually over the six decades. During the first two decades, P yield had the largest deviations in the *Nature* scenario (Fig. 2a–d) while *Grazing* had the lowest. By the third and fourth decades, *Biofuel* had the highest P yield, followed by *Grazing* in decades five and six. The lowest P yields occurring in decades four and five were in *Nature*, followed by *Biofuel* in decade six. Overall, the *Urban* scenario had the smallest deviations in P yield. For all decades and climates, percent deviation in P yield ranged from −23 to +32 ± 13% (S.D.).

The patterns in DDL and TP were similar to P yield. With the exception of the *C3* climate (Fig. 2g and k), the highest deviations in DDL and TP occurred during the first three decades of *Nature*. For the *C1* and *C4* climates, the highest deviations in DDL and TP during the fourth decade occurred in the *Biofuel* scenario. In the fifth and sixth decades, all climates had the largest deviations in DDL and TP occurring in *Grazing*. The lowest values of DDL and TP, signifying the best water quality at the stream and lake scales, occurred first in *Grazing* (roughly decades 1–3), followed by *Nature* in decade four (with the exception of *C4*), and then *Biofuel* in decade 6. Among all decades and climates, percent deviation in DDL ranged from −16 to +25 ± 9%. Percent deviation in TP ranged from −17 to +22 ± 8%.

For similar plots grouped by land use (DEV_C in Eq. (3)), which showed the deviations caused by climate (Fig. 3), percent deviation in P yield, DDL, and TP ranged from −19 to 27 ± 13%, −30 to +45 ± 17%, and −46 to +106 ± 29%, respectively. In ranking the climate decades from best to worst, the best decades were defined as having the lowest *P* values for each indicator, and generally corresponded to the driest decades (Table 1). Conversely, the worst climate decades had the highest P values for each indicator, and generally corresponded to the wettest decades. Trends in the best and worst decades were similar across the three water quality indicators. The worst climate in decade one was *C4*, followed by *C1* in decades three and four, and ending with a combination of *C2* and *C3* in decades five and six. The best climate in decade one occurred in *C3*, whereas all climates in decade 2 had similar effects on the water quality indicators. In decades three and four, *C2* had the best climate, and in decades five and six, C1 had the best climate.

3.3. Relative influences of climate and land use

A visual comparison of the ranges in climate and land use, analyzed at the annual timescale, showed that the influence of land use on P yield, DDL, and TP (Fig. 4a–c), was small initially but then increased by the second and third decade as the cumulative effects of land-use change accrued. The influence of climate on DDL and TP (Fig. 4d–f) was relatively large in the first few years of the simulation time period, small in the second decade, and large again in the third decade. This was because the *C4* climate featured heavy precipitation during the baseline period (2014–2020), and *C1* featured heavy precipitation events in the third decade (Table 1). The effect of heavy precipitation and flooding in both of those decades resulted in increased loads, TP, and ultimately a wide range in results among land use scenarios. A numeric comparison made between the range due to climate and the range due to land use, analyzed at the annual timescale (*R_LU* – *R_CLIM* Eqs. (5) and (6)), showed that for P yield, the range due to land use was greater than the range due to climate in 36 of the 57 simulated years (the difference was greater than zero), whereas the range due to climate was greater in only 21 years (difference was less than zero) (Fig. 5). In contrast, the range in DDL and TP was most often dominated by climate. For DDL, only 3 years had a larger range caused by land use and 54 years had a larger range caused by climate. For TP, 5 years had a larger range in land use and 52 years had a larger range caused by climate. However, ranges in land use and climate were similar in magnitude for DDL and especially for TP during the last several decades, suggesting that the dominance of climate was in fact rather small in most years. This weakened dominance of climate over land use in DDL and TP in the later decades was due to the smaller range among the climate scenarios driven by relatively dry conditions that were coincidentally common to the four scenarios (Table 1).

3.4. P balance

Terrestrial phosphorus supply within Agro-IBIS is governed by the net balance of P inputs and outputs to the soil system. P supply is a critical driver of watershed P dynamics (Motew et al., 2017), and serves as the primary mechanism by which land use may affect water quality. (Land cover type may be considered a secondary driver since it dictates nutrient inputs and outputs.) For ease of analysis, we grouped P inputs and outputs into a composite variable, PBal (for P balance), equal to manure P application rate + fertilizer P application rate – harvest P rate. Simple linear regressions of PBal with P yield, DDL, and TP, revealed statistically significant relationships for each ($p < 0.05$). R^2 was 0.82, 0.62, and 0.33, for P yield, DDL, and TP, respectively.

The decadal trajectory of PBal was consistent with trajectories of P yield, DDL, and TP (Fig. 1). Instances where PBal and water quality indicators diverged suggested there may be delays in the effects of land use. For example, in the *Biofuel* scenario, PBal declined in all decades of the simulation yet P yield, DDL, and TP did not begin declining until the fourth decade (Fig. 1) (TP declined in decade two only because of the strong climatic influence of the first decade). Similarly, PBal had a steep drop in the *Nature* scenario during decade two, yet DDL and TP did not begin to decline until decade three. These results suggest there may be delays in the effects field-based interventions have on water quality, particularly in streams and lakes.

3.5. Sediment P and dissolved P yield

Decadal trends in sediment P and dissolved P yield varied among the land use scenarios and highlighted how different factors control cycling and transport of each form (Fig. 6). For *Nature*, dissolved P yield was greater than sediment P yield throughout all decades due to high rates of PBal during the first several decades (Fig. 1d) and the legacy effects of elevated soil P in the decades following. *Nature* featured low sediment P loss after the third decade due to the regeneration of perennial vegetation, but by the last decade of *Nature*, in which some humans had resettled in the watershed and begun farming, water quality worsened. In *Grazing*, the conversion to pasture kept sediment P relatively low, but the continual additions of manure caused PBal to remain high. The last three decades of *Grazing* thus featured the highest rate of either form of P yield (dissolved in this case) among all land use scenarios. In *Biofuel*, the first three decades saw relatively high rates of dissolved P yield attributable to a combination of high soil P and the slow adoption of fertilizer and manure reductions. By decade six however, *Biofuel* had the lowest P yield of all land use scenarios (Fig. 1), evidenced by the sharp reductions in both sediment and dissolved P in the last three decades (Fig. 6d). Conversion to perennial biofuels with low inputs and high harvest rates gave *Biofuel* a negative PBal in addition to a low risk of erosion. These two factors together gave *Biofuel* the best decade of water quality observed among all land use scenarios.

4. Discussion

4.1. Land use versus climate

Our study identified climate as the dominant influence on all water quality indicators examined. However, our findings also showed that local management plays a key role in future outcomes, independent from the role of climate. The impact of land use, driven chiefly by the net P balance on farms, was (1) substantial in magnitude, evidenced by percent deviations from a climate-averaged mean ranging from −23 to +32%, −16 to +25%, and −17 to +22%, for P yield, DDL, and

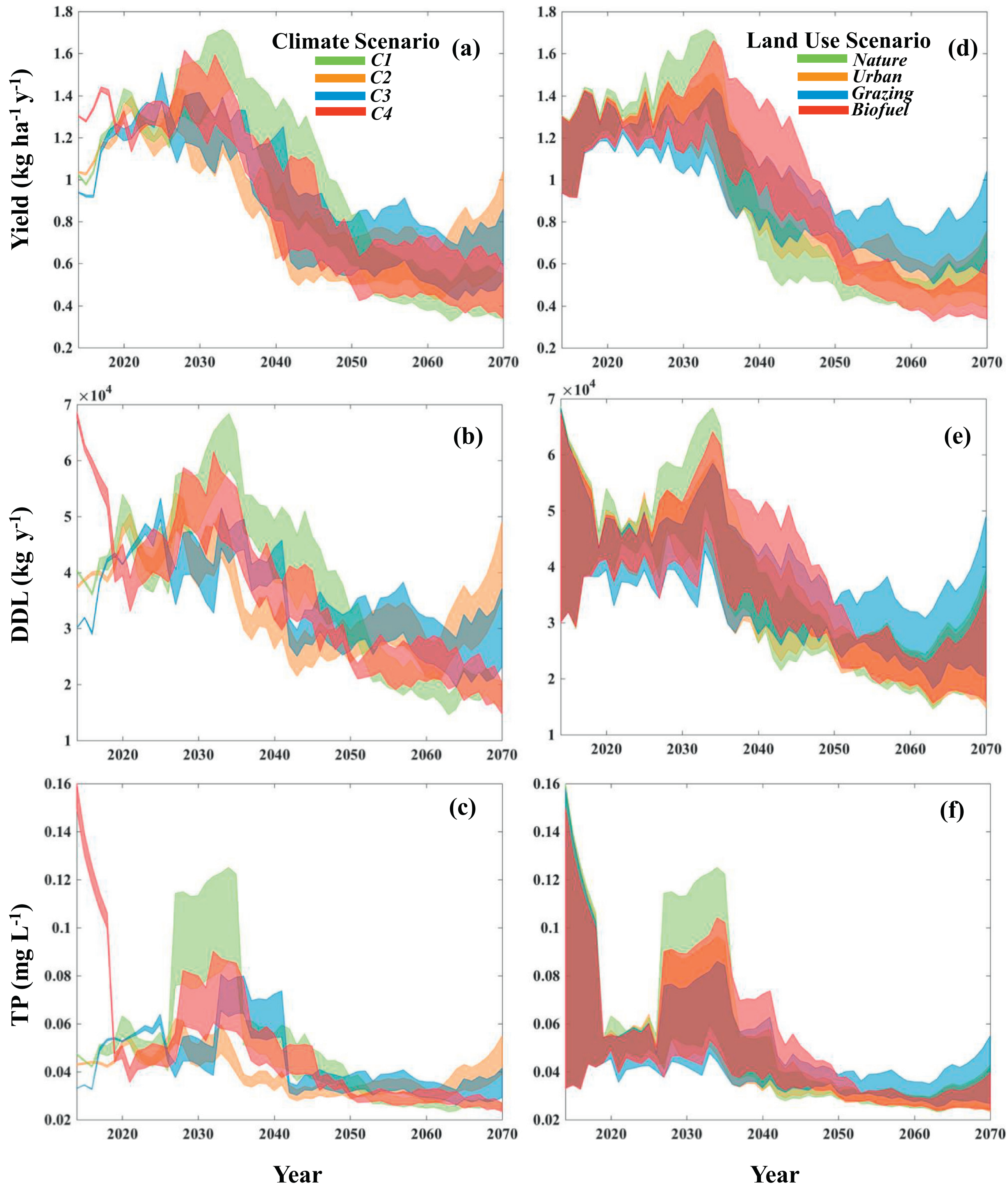

Fig. 4. Annual water quality indicators. Vertical shaded regions denote the range between the maximum and minimum values among the four land use scenarios for a given climate (a-c) and the four climate scenarios for a given land use (d-f).

TP, respectively (Fig. 2); (2) consistent across the four future climate scenarios, as indicated by similar temporal trends in percent deviations from a climate-averaged mean (Fig. 2); and (3) potentially delayed in its effect on stream and lake ecosystems (Fig. 1). These results suggest that while climate may be dominant, local land use plays a vital role in determining future outcomes of water quality in agricultural watersheds, and the effects of local management can be anticipated under a changing climate.

The dominant influence of climate on stream loads and lake P concentration may reflect the high amount of legacy P stored in watershed soils (Bennett et al., 1999; Kara et al., 2012; Motew et al., 2017). High soil P results in high P yield, and because soil P varies slowly, with

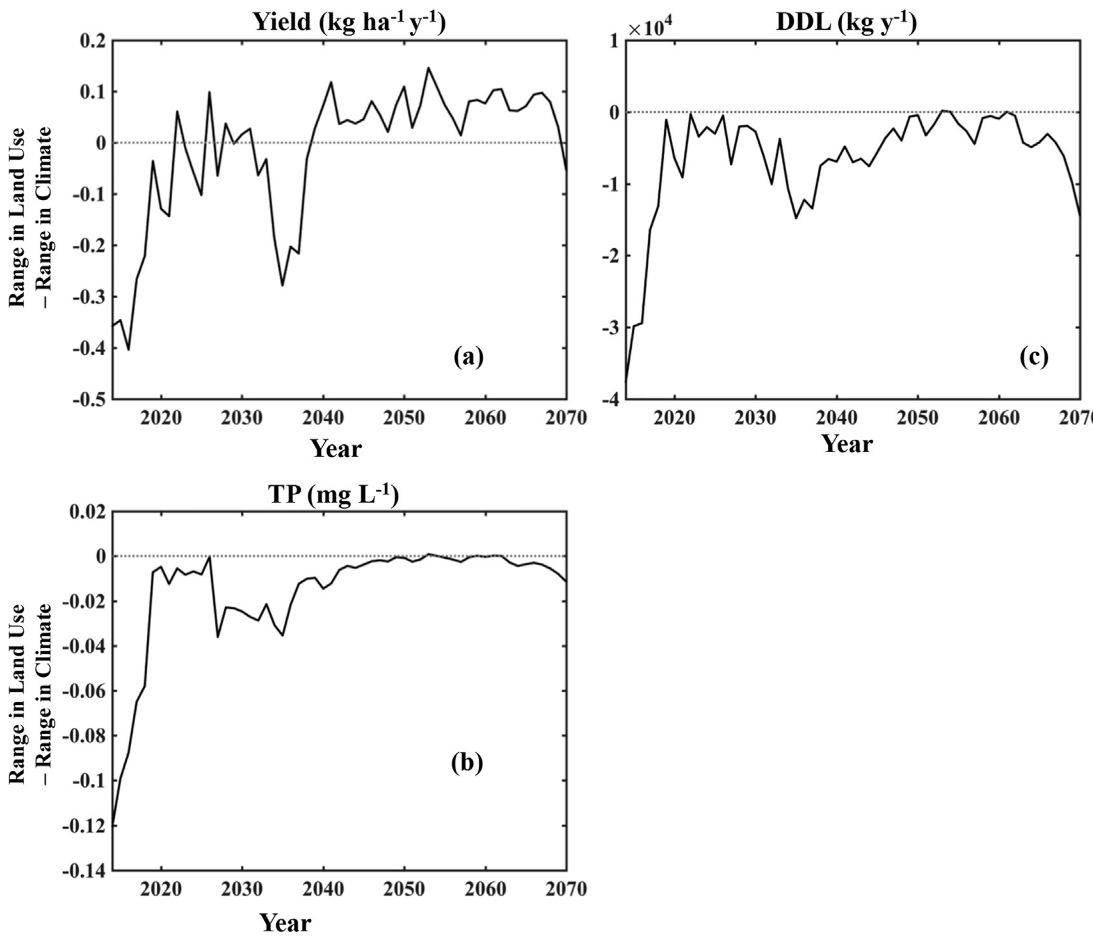

Fig. 5. Mean range across land use minus the mean range across climate, where range is the difference between the maximum and minimum values for the four respective scenarios. Years with positive (negative) values indicate the mean range in land use (climate) was greater.

residence times of decades to centuries, large amounts of P are released to waterways each year. Thus at the annual timescale, stream loading and lake TP concentration will be more sensitive to variations in climate than to management. On fields where the effects of management are more direct, for instance in how annual fertilizer rate or tillage practices may affect soil P, climate and land use may share comparable roles in driving inter-annual variation in P yield. The greater importance of climate in driving stream and lake P dynamics is consistent with previous

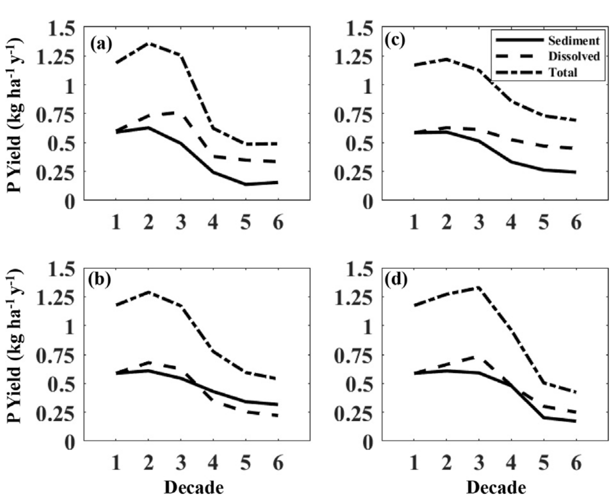

Fig. 6. Mean annual P yield per decade for each land use scenario, *Nature*(a), *Urban*(b), *Grazing*(c), and *Biofuel*(d).

observations that precipitation is a dominant driver of inter-annual variability in P loading to the Yahara lake chain (Carpenter et al., 2014; Carpenter and Lathrop, 2014; Carpenter et al., 2018); model results showing that the climate has a larger impact on watershed-scale runoff than that of land use in the Yahara River watershed (Zipper et al., 2018), as well as other studies that have linked nutrient loading to riverine discharge rates (McElroy et al., 1976; Williams and Hann, 1978; Littlewood, 1995; Correll et al., 1999; Royer et al., 2006). Previous studies have also shown that the effectiveness of field scale management practices in improving water quality varies widely within and among watersheds (Baker and Richards, 2002; Jordan et al., 2005, 2007; Sharpley et al., 2009; Fiener and Auerswald, 2009; Carvin et al., 2018). The greater influence of climate in stream and lake ecosystems may help explain why traditional BMPs (e.g. vegetative buffers, no-till, etc.) are often successful at stemming P loss at the field scale, but not as successful in improving downstream water quality and ecology (Sharpley et al., 2009, Jarvie et al., 2013a, 2013b). A greater influence of climate may help explain why in places such as the Lake Mendota Watershed where more frequent extreme events in recent decades have coincided with increased implementation of BMPs, there has been no reduction in lake P loads and thus improvement in lake water quality (Gillon et al., 2016).

Water quality responded differently to climate and land use depending on how wet or dry conditions were. For example, during very wet decades, such as the third decade of *Nature*, the effects of land use were generally weak (Supp. Fig. 1), indicating that climate may overwhelm land use during periods of flooding and high rainfall. In contrast, the effects of land use were more pronounced in dry years, and water quality was better (Fig. 5, Table 1, Supp. Fig. 1). This agrees with previous observations of Lake Mendota showing that during drought years water quality is improved (Lathrop and Carpenter, 2013). Our results are also consistent with a recent study of Wisconsin lakes (Rose et al., 2017) showing that annual precipitation modulates the dominant landscape features affecting water quality: during dry years, watershed features such as percent land use/land cover in agriculture are more important predictors of lake water quality than in wet years.

Despite temporary improvements in lake water quality during dry years, future climate projections for the region predict increases in average annual precipitation, as well as a greater frequency of extreme precipitation events (WICCI, 2011; Villarini et al., 2013). Extreme events are responsible for a disproportionate amount of annual P loading (Carpenter et al., 2014), can overwhelm traditional conservation practices (Woznicki et al., 2011), and may exacerbate losses of P from landscape hot spots (Motew et al., 2018; Qiu et al., 2019). Thus, while local land use and management will play an important role in determining future water quality in Lake Mendota, there is still a pressing need to address global climate change.

4.2. Importance of P mass balance

The best/worst outcomes of P yield attributable to land use in each decade were dependent on the mass balance of P inputs and outputs to the soil-vegetation system. The importance of balancing inputs and outputs, i.e. manure and fertilizer applications in conjunction with harvest/removal rates, superseded erosion risk. This was demonstrated in the *Grazing* scenario which scenario featured widespread conversion of row crops to perennial pasture throughout the watershed, and a subsequent decrease in erosion risk and sediment P yield. However, the presence of grazing cattle, represented in the model by their consumption of plant P and manure additions, resulted in relatively large losses of dissolved P and total P yield during the last three decades. This is because cycling of P between soil, plant, and animal did not allow for significant drawdown of already-high soil P levels. *Biofuel* also featured a conversion to a perennial landscape. However, the high removal rate of the biofuel crop (to a location outside the watershed), with no new additions of P to the soil, allowed for drawdown of soil P reserves and a marked decrease in dissolved P loss (Fig. 6). Reductions in both sediment and dissolved P loss contributed to *Biofuel* having the best observed water quality outcomes of all simulations in the final decade.

The greater importance of PBal over erosion risk was also evident in the *Nature* scenario, which featured a widespread conversion of cropland to grassland. Despite a significant reduction in erosion risk, dissolved P losses remained high for decades due to the release of soil legacy P. The P-rich ecosystems of *Nature* were also vulnerable to excessive P loss during times of extreme precipitation (e.g. decade three of the *C1* climate, Table 1 and Fig. 3). Conservation practices that focus on stemming erosion would likely not have reduced erosion any more than a conversion to grassland. It can thus be argued that erosion mitigation measures would not have counteracted the high levels of dissolved P loss that occurred in *Nature*. This assertion is supported by other studies that show when erosion is reduced on agricultural lands, dissolved P loss can still be substantial (Bundy et al., 2001; Kleinman et al., 2008). Reducing the overall P budget at the field scale appeared to be a robust approach for limiting P yield in both *Grazing* and *Nature*, even during periods of extreme precipitation (Fig. 1). This finding is supported by research suggesting that reducing terrestrial P supply has protective effects on water quality during periods of extreme precipitation (Motew et al., 2017, 2018).

The importance of terrestrial P supply in affecting water quality is supported by a broad literature linking agricultural sources of P to water quality indicators at field (Kleinman et al., 2002; Kurz et al., 2005), stream and river (Johnson et al., 1997; David and Gentry, 2000), lake (Bennett et al., 1999; Michalak et al., 2013), watershed (Correll et al., 1999; Tong and Chen, 2002; Yuan et al., 2013), and basin (Turner and Rabalais, 1991) scales. Reducing or eliminating the over-application of P to the landscape is important for limiting the buildup of legacy P, which is associated with elevated levels of soil test P and high losses of P in surface runoff (Sharpley et al., 1994; Andraski and Bundy, 2003; Vadas et al., 2005), as well as subsurface flows (Heathwaite and Dils, 2000; Simard et al., 2000). Our results are consistent with previous observations that legacy P can affect downstream water quality outcomes over timescales of years to decades (Jarvie et al., 2013a, 2013b; Powers et al., 2016; McCrackin et al., 2018). The risk for slow release and transport of legacy P, already a problem in the Yahara (Motew et al., 2017), underscores the need for the removal of P from the soil-vegetation system.

4.3. Management implications

Each of the three water quality indicators represents a culmination of unique biophysical processes and timescales within the watershed, each of which can be differentially impacted by land use and climate. Average landscape P yield, represented as an output flux in Agro-IBIS and calculated on a per-hectare basis, was more affected by land use than climate. Conversely, P dynamics within the aquatic system, including total P in streamflow (a flux in THMB) and total P concentration in the lake (a pool in the Yahara WQ Model), were more affected by climate, with the climatic effects greatest in the lake. This suggests that the effects of land use interventions attenuate when moving off the field into streams and lakes, and thus reductions in P loss achieved at the field scale may have a muted effect downstream. This result may have important implications for managers and researchers wishing to estimate downstream water quality changes in response to upstream management interventions. This may be an especially important issue for U.S. watershed management under the Clean Water Act, for example in meeting Total Maximum Daily Load requirements. Out study has identified that the downstream effects of land use are attenuated, but future studies should attempt to quantify how rates of P yield and alternative management practices correspond to downstream P loads and concentrations.

Trends in land use interventions (represented by PBal) and water quality indicators suggested there may be (at least) a 1-decade lag between interventions and water quality response (Fig. 1). Such lags may reflect the slow nature of soil P dynamics (Penn et al., 2014; Vadas et al., 2018) and the slow transport of P from the landscape and through the stream network (Bennett et al., 1999; Meals et al., 2010). The importance of decadal scale lags should be relevant for watershed managers who wish to set realistic expectations for water quality improvements by recognizing there may be delays between management interventions and stream and lake water quality response. Future research should examine whether and/or how much of these lags originate within the soil and stream systems, and how mediating factors such as climate play a role.

A mass-balance approach to nutrient management that aims to reduce legacy P stores promises direct improvements to water quality and may help protect against the effects of increasing precipitation and frequency of extreme events (Motew et al., 2018). First and foremost, there should be emphasis placed on avoiding excess P applications on farms. Increased monitoring and crediting of soil test P could help prevent applications to areas of farms that already have sufficient soil P to support crops. Advancements in farm technologies may also play a role, such as precision manure spreading that allows exact rates of P to be applied to specific areas of a field (Cabot et al., 2006). Then, growing harvestable vegetation with high P uptake rates in areas of P overabundance may help draw down soil P to agronomic levels over the span of years to decades, rather than centuries (McCollum, 1991; Schulte et al., 2010). Within aquatic ecosystems, methods of immobilizing waterborne P (Rydin et al., 2000, Kopacek et al., 2005) or dredging of sediment P (Van der Does et al., 1992) may help reduce legacy P stores that are subject to re-entrainment and/or internal recycling (Søndergaard et al., 2003).

Ultimately, the overall amount of P applied may be the most important consideration when it comes to management strategies, as opposed to practices designed to contain manure on fields. It will be important for resource managers, policy makers, and agricultural professionals to understand the inherent biophysical delays in watershed P transport since water quality improvements due to land use may take decades to manifest. Good and bad water quality years will continue to occur despite the lag, but these are often highly correlated with fluctuations in precipitation (Lathrop and Carpenter, 2013).

4.4. Study limitations

Even though the land use scenarios used in this study included many different field scale combinations of erosion risk, land cover types, nutrient application rates and removal rates, the effects of other management practices were not explicitly examined, such as alternative tillage or incorporation methods (e.g. manure injection: Chen, 2002), the seasonal timing of nutrient applications (Vadas et al., 2011; Collick et al., 2016), or herd management factors. Future research should evaluate the effects of such strategies at the watershed scale because these methods directly affect the amount of surface P available to runoff, as well as the likelihood for high surface P concentrations to coincide with seasonal patterns of precipitation and runoff (e.g. Correll et al., 1999; Royer et al., 2006).

Despite covering a wide variety of land use and climate outcomes over a 57-year period, our results were dependent on the designed scenarios and did not cover the full range of possible water quality responses to land use and climate. Each model simulation was computationally expensive in terms of time to run and data storage requirements (two days and 2 TB per simulation, respectively). Thus, choosing a limited number of highly contrasting scenarios provided an approach for generating a wide range of water quality states caused by climate and land use. In the future as computational power and storage improve, stochastic approaches that explore a fuller range of climate and land use combinations may be possible.

5. Conclusion

We examined the independent effects of land use and climate on surface water quality indicators over six decades in a representative agricultural watershed. Climate had the stronger influence overall, overwhelming the effects of land use at the inter-annual timescale and during wet periods especially, but land use was still an important predictor of water quality at the decadal timescale. The effects of land use were more pronounced in dry years, and attenuated when moving from the field to stream and lake ecosystems, suggesting a challenge for land use to influence downstream water quality. However, because land-use effects were consistent under four contrasting climates, the effects of local management on water quality indicators can be anticipated in the future under a changing climate.

Net P balance on the landscape was a robust driver of water quality outcomes. Thus, reducing manure and fertilizer applications may be the best land use strategy for improving lake water quality in this watershed. Strategies to block nutrient transport from land to waterways may be less effective, since perennial land cover types with low erosion risk may still be susceptible to high losses of dissolved P when legacy P is high. We conclude that land use efforts should focus on reducing excessive inputs of P on farms and achieving a negative P balance in order to draw down legacy soil P.

CRediT authorship contribution statement

Melissa Motew: Conceptualization, Methodology, Software, Investigation, Visualization, Writing - original draft, Writing - review & editing. **Xi Chen:** Methodology, Software, Writing - review & editing. **Stephen R. Carpenter:** Methodology, Software, Writing - review & editing. **Eric G. Booth:** Methodology, Software, Writing - review & editing. **Jenny Seifert:** Methodology. **Jiangxiao Qiu:** Methodology, Software, Writing - review & editing. **Steven P. Loheide:** Writing - review & editing. **Monica G. Turner:** Writing - review & editing. **Samuel C. Zipper:** Methodology, Software, Writing - review & editing. **Christopher J. Kucharik:** Methodology, Software, Supervision, Funding acquisition, Writing - review & editing.

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Appendix A. Supplementary data

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